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A COMPARATIVE STUDY ON THE METHODS OF COMPUTING PIVOT POINTS USING LOGISTIC REGRESSION

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ABSTRACT

Proper prediction of potential turning points is the key to success for the traders in futures, commodities, and stock markets. Many technical analysis tools serve this purpose and one such tool is the pivot point. It is used by the traders to predict the support and resistance level in the current and upcoming trading sessions. The standard pivot point, in general, is the simple average of low, high, and close prices of the previous trading session. However, some other variations to this approach are in practice. This work applies logistic regression to compare the performances of the pivot points computed using Standard method, Woodie's method and DeMark's method. With the pivot points computed with these three methods, the categorical trend variables are generated. Since using multiple indicators is a common practice, identification of the most competing method of computing the pivot becomes necessary. This study utilizes Logistic Regression analysis to identify the most competing method of pivot to be used with other technical indicators. The credibility of the results is tested with various performance measures and out of sample tests of the fitted logistic regression models.

Keywords: Pivot Point, DeMark's Pivot, Woodie's Pivot, Bootstrapping, Logistic Regression, Chaikin's Oscillator, Relative Strength Index

INTRODUCTION

The information on the previous session's High price and Low price helps in understanding the intricacies of price movements in a better manner. They along with the Close price and the Open price play a significant role in deciding the trend. All these features are combined in a scientific way to form a pivot point which throws more light on the direction of price movements. Thus, a pivot point is an indicator of technical analysis mainly used for determining the overall trend of the market over different time frames. On any subsequent day, trading above the pivot point indicates the ongoing bullish sentiment and the trader can plan to buy, while trading under the level pivot point shows bearish sentiment and the trader can think of shorting. Unlike the moving averages or oscillators, the pivot points are static and remain at the same level throughout the trading session. It means that largest price movement is expected to occur at this price. The pivot point is the basis on which the support and resistance levels are projected. These levels help the trader to determine the entry and points of exit in order to stop the losses or make the profit. It is believed that at these levels the price interaction causes a reaction. Various methods of computing the pivot points are in practice. In this work three different methods of computing the pivot points are compared using multiple indicators.

Almost all traders use technical trading indicators to identify the most promising points of entry and exit. The technical indicators are broadly classified as trend, volume, momentum, and volatility indicators. The use of too many indicators leads to inefficient decisions. In order to optimize the usage of indicators, redundancy should be avoided. An improper combination leads to the multiple counting of the same information. A good combination should contain indicators that complement each other. This can be done by selecting one indicator from each class of indicators. Since each class aims to provide a different interpretation of market conditions, inclusion of one from each class avoids redundancy. The credibility of any combination of technical indicators can be tested with statistical models.

The standard pivot point is the simple average of high, low and close prices of the previous trading session. However, some other variations to this approach are in practice. The close price level of stock market delivers very significant information about the overall behavior of the traders. It states a lot about the thinking of big investors who allot large sum of money into the stock market for the purposes of asset management. The second approach considered in this study is the Woodies approach which is not a simple average. This approach gives more weight to the previous session's close price. Yet another pivot point was developed by Tom DeMark, the founder and CEO of DeMark analytics. In this method conditional pivots are computed by comparing the previous open and close prices.

Stock price forecasting is of great importance in financial markets. Numerous prediction models have emerged to achieve this. These models act as a guide to the trader in trading decisions. The Classical linear regression model provides avenues to forecast the share prices. Instead if we have a model which directly indicates the direction of the movement of the share prices, the result may help the trader to make quick decisions. To achieve this goal, Non-Linear models are used in this study.

LITERATURE REVIEW

According to Lee (2004), Logistic Regression, which is supportive for the estimate of the occurrence or absence of an outcome based on values of a set of predictor variables, is used in the range of commercial finance, banking and investments. Many researchers used Multivariate Discriminant Analysis for the default-prediction model. It was used as a default prediction model by Altman (1968) to classify the firms. In predicting financial suffering and bankruptcy which have been extensively applied as the evaluation models providing credit-risk information, Logistic Regression was used by Ohlson (1980) which was then trailed by several authors such as Zavgren (1985). Later the same drift was chosen by Zmijewski (1984) for a Probit Analysis.

Horrigan (1965) found monetary ratios as positive predictors for bond rating. The conference, Business Risk Homogeneity: A Multivariate Application and Evaluation by Melnyk & Iqbal (1972) used ratios to classify companies into similar risk groups and tried to recount them to the companies' market rates of return but they could not report promising outcomes.

Connar (1973) studied total liabilities to net worth, working capital to sales, cash flow to number of common shares, earnings per share to price per share and current liabilities to inventory, but found them to be poor pointers of return on common stock.

Kumar & Ravi (2007) carried out a complete review on numerous works connected to the glitches related to the prediction of bankruptcy. They designated that neural network is most extensively used method followed by statistical models. McConnell, Haslem & Gibson (1986) have recognized that qualitative data can deliver supplementary evidence to forecast the presentation of stock price more precisely.

Logistic Regression technique used by Huang, Cai & Peng (2007) uses important factors as explanatory variables. Logistic Regression Models (LRM) with two or more descriptive variables are broadly used in exercise (Haines *et al.*, 2007). The restrictions of the LRM are normally projected by extreme probability (Pardo, Pardo & Pardo, 2005).

In Logistic Regression, the predictor values from the study can be understood as probabilities (0 or 1 outcome) or membership in the target groups (categorical dependent variables). It has been detected that the probability of a 0 or 1 result is a non-liner function of the logit (Nepal, 2003).

Logistic Regression is beneficial for circumstances in which it is obligatory to forecast the occurrence or absence of a characteristic or conclusion based on standards of a set of predictor variables. It can be used to evaluate odd ratios for each of the independent variables in the model. It supports to formulate a multivariate regression between a dependent variable and some independent variables (Lee, Ryu & Kim, 2007). It is intended to evaluate the constraints of a multivariate explanatory model in conditions where the dependent variable is dichotomous, and the independent variables are categorical or continuous.

RESEARCH METHODOLOGY

Types of Pivot Points Considered in This Work:

Let us code previous Close price as C, previous Open price as O, previous Low price as L and previous High price as H.

i Standard Pivot Point:

Standard Pivot Point is the most basic Pivot Point. It is the simple average of High, Low and Close from a prior period.

ii Woodie's Pivot Point:

This approach is a weighted average which assigns more weight to the close price.

$PP = (H + L + 2C) / 4$

iii Demark Pivot Point:

Demark Pivot Points start with a different base and use different formulas for support and resistance. These Pivot Points are conditional on the relationship between the close and the open.

If $C < O$, then $X = H + (2 X L) + C$

If $C > O$, then $X = (2 X H) + L + C$

If $C = O$, then $X = H + L + (2 X C)$

Pivot point $= X / 4$

Technical Indicators Considered in This Work:

The main aim of this work is to compare the pivot points computed using the three methods. But using a single indicator as a market monitor may not be an effective practice. Hence multiple indicators are used in this work to identify the more competing pivot. A multi-indicator strategy may become redundant when they provide same type of information. Selection of one indicator from each broad category of technical indicators may be an effective way of avoiding this fallacy. With this realization this work considers the following technical indicators to analyze the performance of the three types of pivots.

Trend Indicator-Moving Average Convergence-Divergence:

Moving Average Convergence Divergence (MACD) is considered as a leading indicator, but with a bit of lag. It is calculated as the difference of 26-period Exponential Moving average and 12-period Exponential Moving Average. The MACD suggest a buy sign when the MACD line crosses overhead the indication line or the MACD line crosses above the nil line. However, a sell indicator is also created when the MACD line crosses below the signal line or crosses down the zero line.

Momentum Indicator-Relatives Strength Index:

Relative Strength Index (RSI) is a leading indicator that helps to measure the speed and the price movement. RSI, which is a kind of momentum oscillators used to calculate the market recent gains against its recent losses and translates that information into a number between 0 and 100, oscillates between 0 and 100. The value of RSI is considered overbought when above 70 and oversold when below 30.

Volume Indicator-Chaikin Oscillator:

Chaikin Oscillator measures the momentum of the accumulation delivery line using the MACD formula. It is the difference between the 3-day and 10-day Exponential Moving Averages of the accumulation distribution line. This indicator is not based on stock price. High volume points to a high interest in an instrument at its current price and vice versa. If the stock price is shows increasing but the volume is going down it means that their fewer investor buying at a higher price. Therefore, it can give a signal that potential change in direction of the stock price.

Volatility Indicator-Average True Range:

The Average True Range is considered as an accurate volatility measure. It measures the intensity of movement of an asset in the past.

Classification Method:

The aim of this work is to compare the categorical trend variables generated using three different types of pivots. Since the idea is to analyze the affiliation between the categorical dependent variable and the selected technical indicators, it is necessary to have a classification algorithm to achieve the objective. Classification is a method where we can classify data into a given number of classes. The foremost goal of a classification problem is to recognize the category/class to which a new data will fall under. A restraint of ordinary linear models is the requirement that the dependent variable is numerical rather than categorical. But a range of techniques for analyzing data with categorical dependent variables have been developed. The techniques include Bayes classifier, K-nearest Neighbor, Decision Trees, Discriminant Function and Logistic Regression. Among these methods the Binary Logistic Regression is the most suitable method for the present study.

Logistic regression is a mechanism learning procedure for classification. In this system, the probabilities relating to the possible results of a single trial are shown using a logistic purpose. The Binary Logistic Regression model is an improvement of linear regression. The logistic model best suits the situation in which

- The dependent variable is a dichotomous variable.
- The relationship between the independent and dependent variables is not linear.
- The distribution of the variables is not known. (not necessarily normal).
- The prior probability of failures is not available.

The Binary Logistic Regression accommodates both separate and unceasing explanatory variables. It can be used to forecast a categorical dependent variable and to determine the percentage of dependent variable adjustment explained by the independent variables. It achieves the same task of Linear Discriminant Analysis. But the Logistic model uses a Sigmoid function that offers an output between 0 and 1. This aspect makes it appropriate for financial studies on stock market movements and Bankruptcy. The Logistic model uses a probabilistic method based on maximum likelihood estimators with no parametric assumptions. In this point of view, the Logistic regression is more robust method. The model for Logistic regression is

$$\pi(x) = p(Y = 1\ given\ X = x) = \frac{\exp(\beta_0 + \sum_{i=1}^{p} \beta_i X_i)}{1 + \exp(\beta_0 + \sum_{i=1}^{p} \beta_i X_i)} - - - (1)$$

For two classes of output Y, the parameters β_0, β_1,----β_p are estimated using Maximum Likelihood estimation. The Logit is given by

$$G(x) = log \frac{\pi(x)}{1-\pi(x)}\ log \frac{P(Y=1\ given\ X=x)}{P(Y=0\ given\ X=0)} = \beta_0 + \sum_{i=1}^{p} \beta_i X_i - - - (2)$$

The curve of π(x) is called Sigmoid. It is because it results in a S-Shaped nonlinear curve. Thus, the model introduces an appropriate link function in the analysis. This model is more relevant when the dataset is very large. This model estimates the logit of Y from X. The logit is the natural logarithm of the odds ratio. The odds ratio is given by

$$\frac{\pi(x_i)}{1-\pi(x_i)} - - - - - - - - - - - - - - - - - (3)$$

The nonlinear probability models forecast the share price by means of price likelihood

$$p(Z) = \frac{1}{1+e^{-Z}} + \varepsilon_i - - - - - - - - - - - - (4)$$

Here Z= X^T β. This is a linear function of the explanatory variables. P(Z) always varies between 0 and 1. When P(Z) = 0.5, then it is an approximate point for price direction separation. A logistic function is used in the logit model instead of standard normal function. In Logit model,

$$P(Z \leq z) = \frac{e^z}{1+e^z} = G(z) - - - - - - - - - - - - (5)$$

Evaluations of a Logistic Regression Model:

In this work the credibility of a Logistic regression model is tested based on the following:

- Overall evaluation of the model by comparing the model with the null model using Likelihood Ratio Test (LRT).
- Test for multicollinearity using the Variance Inflation Factors.
- Statistical tests of the individual predictors using Wald test.
- Testing the model with McFadden's R2 value.
- Goodness of fit using Hosmer-Lemeshow test statistic.
- Validation of predicted results using C, Dxy, gamma and Tau-a statistic values.
- Assessment of the predicted probabilities with Bootstrapping.

RESULTS & DISCUSSION

The study uses the Logistic Regression technique to predict stock price movement. The regular high price, low price, open price, close price, no. of shares traded and turnover of the NSE index NIFTY50 from January 2015 to July 2019 collected from the official website of National Stock Exchange is used in this study. The 1000 observations from 1st January 2015 to 15th June 2019 are used as training data and the data from 16th January 2019 to 31st July 2019 are used as testing data. The pivot points are computed using the Standard approach, Woodie's approach and DeMark's approach. These pivot points are used to generate the dependent variable. If the close price is greater than pivot point, the trend value is 1 and otherwise it is 0. The trend variables are the dependent variables in this study.

Models Fitted:

- Model I: A Logistic Regression model with the trend of the Standard Pivot(strend) as the dependent variable and RSI, ATR, MACD and Chaikins Volume oscillator(vol) as predictors.
- Model II: A Logistic Regression model with the trend of the DeMark's Pivot(dtrend) as the dependent variable and RSI, ATR, MACD and Chaikins Volume oscillator(vol) as predictors.
- Model III: A Logistic Regression model with the trend of Woodie's Pivot(strend) as the dependent variable and RSI, ATR, MACD and Chaikins Volume oscillator(vol) as predictors.

Overall Evaluation of the Models:

A logistic model is supposed to offer an improved fit to the data if it establishes an enhancement over the null model which is also called an intercept-only model. An intercept-only model serves as a good baseline because it contains no predictors. Subsequently, all explanations, according to this model, would be foretold to belong in the largest outcome category. An improvement over this baseline is examined by using the likelihood ratio test. For all the three models p value is less than 0.05 as indicated in Table-1 and thus the fitted models are better than the null model.

Table 1: Comparative Analysis of the Fitted Models with Null Models

Dependent variable	Results of LRT test
Strend (Model I)	Analysis of Deviance Table Model 1: strend ~ RSI + macd + vol + ATR Model 2: strend ~ 1 Resid. Df Resid. Dev Df Deviance Pr(>Chi) 1 970 1101.5 2 974 1347.0 -4 -245.5 < 2.2e-16 *** --- Signif. codes:0‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Dtrend (Model II)	Analysis of Deviance Table Model 1: dtrend ~ RSI + macd + vol + ATR Model 2: dtrend ~ 1 Resid. Df Resid. Dev Df Deviance Pr(>Chi) 1 970 1090.1 2 974 1343.9 -4 -253.74 < 2.2e-16 *** --- Signif. codes:0‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Wtrend (Model III)	Analysis of Deviance Table Model 1: wtrend ~ RSI + macd + vol + ATR Model 2: wtrend ~ 1 Resid. Df Resid. Dev Df Deviance Pr(>Chi) 1 970 1233.8 2 974 1351.5 -4 -117.74 < 2.2e-16 *** --- Signif. codes:0‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Test for Multicollinearity:

The variance inflation factor (VIF) counts the amount of correlation between one predictor and the other predictors in a model. It is used for diagnosing multicollinearity. There are some guidelines whether the VIFs are in an acceptable range. A rule of thumb commonly used in practice is if a VIF is > 10, the model has multicollinearity. For the models fitted all the VIF values are less than 10 as given in Table-2 and hence the indication is that the analysis can be continued with the fitted models.

Table 2: Variance Inflation Factor of the Predictors

Dependent variable	VIF
Strend (Model I)	RSI macd vol ATR 3.605124 5.686678 1.848737 1.754818
Dtrend (Model II)	RSI macd vol ATR 3.518943 5.521926 1.826609 1.742048
Wtrend (Model III)	RSI macd vol ATR 2.964133 4.829430 1.831162 1.670899

Statistical Tests of the Individual Predictors:

The statistical implication of distinct regression coefficients is tested using the Wald chi-square statistic. If the p-values are <0.05, the predictors are significant. For all the three models the *p* values of all the predictors are less than 0.05 as shown in table 3.

Table 3: Test for Significance of the Coefficients

Dependent Variable	Logistic Regression Model Results
Strend (Model I)	Coef S.E. Wald Z Pr(>|Z|) Intercept -2.5211 0.3119 -8.08 <0.0001 RSI 3.1043 0.2559 12.13 <0.0001 macd -0.0219 0.0021 -10.20 <0.0001 vol 2.9209 0.8231 3.55 0.0004 ATR -0.0080 0.0017 -4.70 <0.0001
Dtrend (Model II)	Coef S.E. Wald Z Pr(>|Z|) Intercept -2.7163 0.3182 -8.54 <0.0001 RSI 3.2025 0.2611 12.27 <0.0001 macd -0.0211 0.0021 -9.87 <0.0001 vol 2.6046 0.8258 3.15 0.0016 ATR -0.0070 0.0017 -4.15 <0.0001
Wtrend (Model III)	Coef S.E. Wald Z Pr(>|Z|) Intercept -1.2865 0.269 0 -4.78 <0.0001 RSI 1.5802 0.1939 8.15 <0.0001 macd -0.0135 0.0018 -7.44 <0.0001 vol 3.9481 0.7711 5.12 <0.0001 ATR -0.0047 0.0015 -3.04 0.0024

Test for Goodness of Fit Based on Training Data:

The Hosmer–Lemeshow statistic is a Pearson chi-square statistic, calculated from a 2 X g table of observed and projected predictable occurrences, where g is the number of groups formed from the estimated likelihoods. In Table-4, for all the three models p values are greater than 0.05. But it is the greatest for DeMark's trend variable.

Table 4: Results of Goodness of Fit

Dependent Variable	Hosmer and Lemeshow goodness of fit (GOF) test
Strend (Model I)	Chi-squared = 15.401, df = 8, *p*-value = 0.0518
Dtrend (Model II)	Chi-squared = 15.401, df = 8, *p*-value = 0.2518
Wtrend (Model III)	Chi-squared = 10.561, df = 8, *p*-value = 0.2278

Validations of Predicted Probabilities:

Logistic regression envisages the logit of an occasion outcome from a set of predictors. Since the logit is the natural log of the odds, it can be changed back to the possibility scale. The subsequent foretold probabilities can then be revalidated with the real significance to govern if high chances are certainly related with events and low possibilities with nonevents. The degree to which predicted probabilities agree with actual consequences is articulated as a degree of association. The four procedures of association are Kendall's Tau-a, Goodman-Kruskal's Gamma, Somers's D statistic, and the c statistic. The Tau-a statistic is Kendall's rank order correlation coefficient without adjustments for ties. The Gamma statistic is grounded on Kendall's coefficient but alters for ties. Gamma is more valuable and apt than Tau-a when there are ties on both outcomes and predicted prospects.

Somers's D is a favored extension of Gamma whereby one variable is designated as the dependent variable and the other the independent variable. The C statistic signifies the number of pairs with different observed outcomes for which the model correctly predicts a higher possibility for explanations with the occurrence outcome than the possibility for nonevent observations. The C statistic ranges from 0.5 to 1. C equal to 0.5 means that the model is no better than assigning observations randomly into outcome categories. C=1 denotes the meaning that the model allocates higher probabilities to all explanations with the event conclusion, compared with nonevent observations. If numerous models were tailored to the same data set, the model chosen as the best model should be linked with the highest C statistic. Thus, the C statistic offers a basis for comparing dissimilar models fitted to the same data. From Table-5, it is understood that the C value for the model II is the uppermost. Also, the Tau-a, Gamma and Dxy are the highest for the model II.

Table 5: Testing the Model Based on Rank Discrimination Indices

Rank Discrimination Indices	Strend (Model I)	Dtrend (Model II)	Wtrend (Model III)
C	0.785	**0.790**	0.700
Dxy	0.569	**0.581**	0.401
Gamma	0.569	**0.581**	0.401
Tau-a	0.284	**0.288**	0.201

Testing Based on R2 Computed with MacFadden Approach:

McFadden's R2 is defined as 1−LLmod/LL0, where LLmod is the log likelihood value for the fitted model and LL0 is the log likelihood for the null model which includes only an intercept as predictor. A model whose McFadeen's R2 is between 0.2 and 0.4 is considered a good model. Here the measure is the greatest for the model with DeMark's trend as the dependent variable:

Table 6: McFadden's R2 Values

Dependent variable	MacFadden R^2
Strend (Model I)	0.28
Dtrend (Model II)	0.29
Wtrend (Model III)	0.18

An Assessment of the Predicted Probabilities:

Bootstrapping is a commanding method for executing statistical tests. In bootstrapping we recurrently sample from the experimented dataset, with replacement, forming a large number of bootstrap datasets, each of the same size as the original data. The impression is that the unique observed data takes the room of the population of interest, and the bootstrap samples represent samples from that population. While bootstrapping, model is fitted to original data and also to each of the bootstrap sample datasets. Then the variability of the point estimates across each of the bootstrap datasets is taken as the modification for the limitation estimation obtained from fitting the model to the original data. According to the consequences in Table-7, the model with Demark's trend as the dependent variable has the least mean squared error.

Table 7: Demark's Trend

Dependent variable	Mean Squared error with Bootstrapped data
Strend (Model I)	Mean squared error=0.00055
Dtrend (Model II)	Mean squared error=0.00024
Wtrend (Model III)	Mean squared error=0.00074

CONCLUSION

To compare the three different methods of computing the pivot points using Logistic Regression, the NSE index NIFTY50 is used in this study. Since the usage of multiple technical indicators is considered a good practice, four indicators are used as predictors. The categorical trend variables generated using the three methods of computing the pivot points are the dependent variables. Three Logistic regression models are fitted and the credibility of the fitted models are analysed using various approaches.

i. The Likelihood ratio test revealed that all the three models are better than intercept-only models.
ii. If the predictors in a model are correlated, the model suffers due to redundancy. The test of multicollinearity for all the three models resulted in Variance Inflation Factors less than 10 which imply that the predictors are not redundant.
iii. The McFaddens R2 value for Model I and Model II lie between 0.2 and 0.4. Further this value is greater for Model II.
iv. The coefficients of all the predictors are significant as revealed by Wald tests.
v. The Hosmer-Lemeshow's chi square statistic is significant for all the three models. It is the greatest for Model II.

vi. The models are validated using association measures. All the indices are greater for Model II.

vii. The predicted probabilities are assessed using Bootstrap samples. The Bootstrap data values produced minimum mean squared error for the Model II.

Based on the above in-sample and out-of sample tests, it is concluded that the usage of DeMark's pivot point is more stable than pivots computed using Standard and Woodie's approach. The result is also theoretically justified since the standard and Woodie's methods are unconditional but DeMark's method is a conditional method of computing the pivot point.

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